

## NOTES AND CORRESPONDENCE

### Predictions of Indian Ocean SST Indices with a Simple Statistical Model: A Null Hypothesis

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#### ABSTRACT

Several recent general circulation model studies discuss the predictability of the Indian Ocean dipole (IOD) mode, suggesting that it is predictable because of coupled ocean–atmosphere interactions in the Indian Ocean. However, it is not clear from these studies how much of the predictability is due to the response to El Niño. It is shown in this note that a simple statistical model that treats the Indian Ocean as a red noise process forced by tropical Pacific SST shows forecast skills comparable to those of recent general circulation model studies. The results also indicate that some of the eastern tropical Indian Ocean SST predictability in recent studies may indeed be beyond the skill of the simple model proposed in this note, indicating that dynamics in the Indian Ocean may have caused this improved predictability in this region. The model further indicates that the IOD index may be the least predictable index of Indian Ocean SST variability. The model is proposed as a null hypothesis for Indian Ocean SST predictions.

#### 1. Introduction

Tropical Indian Ocean sea surface temperature (SST) is an important influence on local- and global-scale climate variability (see Schott et al. 2009 for a review). Recent research focuses mostly on the Indian Ocean dipole (IOD) index as introduced by Saji et al. (1999) and Webster et al. (1999). The general idea is that this index may represent some dynamical climate mode similar to that of the El Niño–Southern Oscillation (ENSO) mode in the tropical Pacific, but intrinsic to the Indian Ocean. It is argued that the IOD could be forced by both Indian Ocean intrinsic ocean dynamics and by remote forcing from ENSO (Fischer et al. 2005; Behera et al. 2006). However, some studies indicate that the IOD index may only be a statistical index, with little indication that it represents something like a coupled climate mode (e.g.,

Baquero-Bernal et al. 2002; Dommenges 2007; Jansen et al. 2009).

Important evidence for a dynamical origin of the IOD index could be the predictability of this index beyond a simple red noise model. The predictability of the Indian Ocean SST and especially the IOD index has been the focus of a series of recent papers (Wajsovicz 2004, 2005; Luo et al. 2007, hereafter LBMY07, 2008, hereafter LBMSY08; Song et al. 2008). LBMY07 and LBMSY08 study the forecasts of the Indian Ocean SST in a coupled ocean–atmosphere general circulation model (CGCM) initialized by an observed data assimilation scheme focused on the predictability of two recent IOD events. LBMSY08 conclude that the IOD events can be predicted three to four seasons ahead, because of Indian Ocean intrinsic ocean dynamics, independent of conditions in the tropical Pacific. They find that the 2006 IOD event that coexists together with a weak El Niño event was more predictable than the 2007 IOD event that had coexisting La Niña conditions in the tropical Pacific. They further argue that the prediction skill for the IOD was due to coupled ocean–atmospheric dynamics

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independent of the tropical Pacific. However, in a recent study Song et al. (2008) find that the IOD events in a CGCM simulation were only predictable in cases where El Niño SST anomaly conditions were present in the tropical Pacific.

It is interesting to note that neither Wajsowicz (2005) nor LBMSY08 quantify the forecast skill of the IOD index itself, but they only discuss the individual poles, which makes it unclear whether or not the IOD index presents an index of Indian Ocean SST that has prediction skill above the skill of the individual poles. More importantly, however, it is unclear from recent publications how much of the forecast skills of the CGCM predictions is due to the response to tropical Pacific SST and how much is due to intrinsic Indian Ocean dynamics, independent of conditions in the tropical Pacific. Although Song et al. (2008) clearly point toward the dominant role of the tropical Pacific SST they do not quantify the forecast skills. It therefore seems adequate to compare the prediction skills of CGCM predictions with a simple null hypothesis model, as done in other such studies (e.g., Latif et al. 1998), to point out the importance of coupled ocean–atmosphere dynamics.

The aim of this study is to provide such a simple forecast model, which can be used as a null hypothesis for Indian Ocean SST prediction skills, against which “dynamical” forecast skills of more complex models can be tested. The aim is to address the following question: what is the forecast correlation skill of a model that is forced by the tropical Pacific SST only and does not include any coupled ocean–atmosphere dynamics in the Indian Ocean? This will be done by a simple statistical model, which is used to forecast Indian Ocean SST indices in 12-month lead using only the information of the current Indian Ocean SST and future tropical Pacific SST. The skill of this model will be evaluated in comparison to recent CGCM results.

#### *a. A simple forecast model*

A commonly used null hypothesis against which forecast skills of prediction schemes are evaluated is the persistence assumption. However, the Indian Ocean SST is known to be significantly influenced by the tropical Pacific SST anomaly conditions (e.g., Venzke et al. 2000; Kug et al. 2004), which also have some significant seasonality. To evaluate the forecast skill resulting from resolved dynamics internal to the Indian ocean–atmosphere system, it would therefore seem reasonable to extend the persistence null hypothesis by some forcing from the tropical Pacific SST anomaly conditions. A simple linear statistical forecast model for the Indian Ocean SST anomalies could therefore be formulated as follows:

TABLE 1. List of the different indices used in this study and their corresponding coordinates.

Index region	Coordinates
EIO	10°S–0°, 90°–110°E
WIO	10°S–10°N, 50°–70°E
CIO	5°S–5°N, 60°–100°E
SWIO	17.5°–7.5°S, 50°–70°E
IOD	WIO–EIO
Niño-3	5°S–5°N, 150°–90°W

$$T_i(t+1) = r_T T_i(t) + r_{Tp} T_p(t), \quad (1)$$

where  $T_i$  is an SST anomaly index in the Indian Ocean,  $T_p$  is the tropical Pacific SST anomalies estimated by the Niño-3 index region (see Table 1 for coordinates), and the time step  $t$  is 1 month. The statistical parameters  $r_T$  and  $r_{Tp}$  are multilinear regression parameters of the simple linear model in Eq. (1). The model is a discrete representation of a temperature tendency equation, such as a simple autoregressive process of the first order with  $T_p$  as the driving forcing. In this model it is assumed that the forcing  $T_p$  acts on the tendencies of  $T_i$  instantaneously, leading to a delay maximum correlation with  $T_i$  itself at some larger time lag due to the inertia of  $T_i$ . The instantaneous forcing of  $T_p$  seems a reasonable assumption, because the atmospheric teleconnections from the Pacific region to the Indian Ocean are relatively fast (shorter than a month). This type of model is also used in Jansen et al. (2009) to highlight the influence of El Niño onto Indian Ocean SST variability. A similar model, but with  $T_p$  regressed onto time-lagged  $T_i$  directly, has also been used in Kug et al. (2004) to point out that El Niño SST leads to a significant amount of predictability in the Indian Ocean.

Note that the model in Eq. (1) assumes stationarity and cannot simulate trends in the data. Trends observed in the Indian Ocean resulting from external forcing such as the anthropogenic forcings must be introduced in terms of an additional model. Therefore, the model parameter estimates used in this study are always based on linear detrended data. The model parameters in Eq. (1) are estimated by a least squares fit to the observed monthly mean SST of the HADISST dataset (Rayner et al. 2003) from 1950 to 2007 for different indices of the tropical Indian Ocean SST (Table 1). The fit is done for each calendar month separately, which allows for seasonal differences in the statistical parameters. Thus, the statistical model consists of 24 empirically estimated parameters.

Figure 1 shows the regression parameters for the different indices as a function of calendar month. In

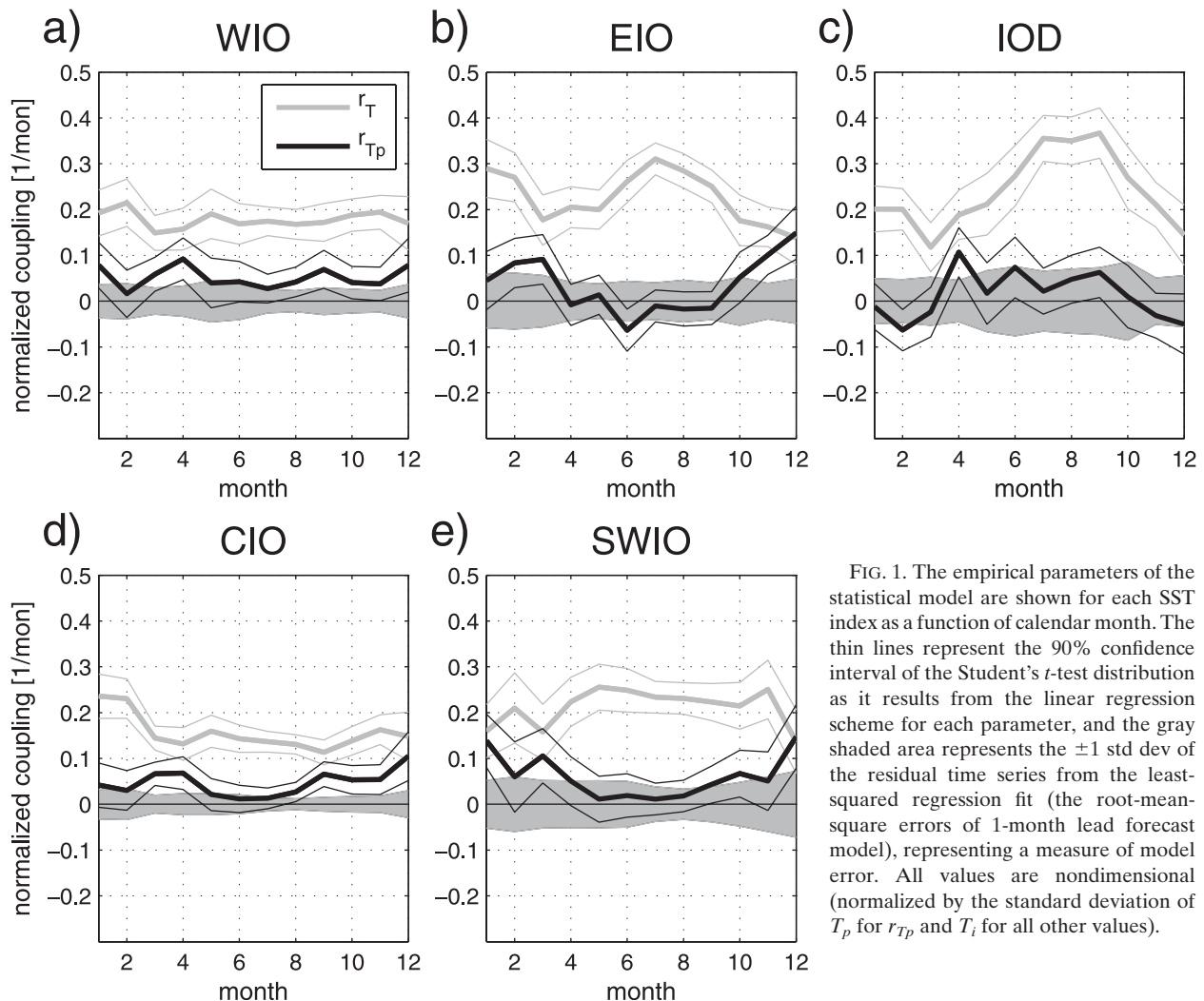


FIG. 1. The empirical parameters of the statistical model are shown for each SST index as a function of calendar month. The thin lines represent the 90% confidence interval of the Student's  $t$ -test distribution as it results from the linear regression scheme for each parameter, and the gray shaded area represents the  $\pm 1$  std dev of the residual time series from the least-squared regression fit (the root-mean-square errors of 1-month lead forecast model), representing a measure of model error. All values are nondimensional (normalized by the standard deviation of  $T_p$  for  $r_{Tp}$  and  $T_i$  for all other values).

addition to the indices motivated by the IOD index we discuss the central Indian Ocean (CIO) index, which should be a good representation of the region in the Indian Ocean that is most strongly forced by El Niño. We further discuss the southwest Indian Ocean (SWIO) index, which is found to be a region of the Indian Ocean that has both a strong climate impact and a potential to have SST variability forced from Indian Ocean intrinsic ocean dynamics independent of El Niño (Xie et al. 2002; Annamalai et al. 2005; Luo et al. 2005; Schott et al. 2009). In all index regions we find a clearly stronger relation to  $T_i$  than to  $T_p$ , simply indicating that the persistence of  $T_i$  is more important than the forcing by  $T_p$ . However, the linear relation to  $T_p$  is statistically significant for all box index regions in at least some calendar months, indicating that all regions are forced by  $T_p$ . The eastern Indian Ocean (EIO) and SWIO region have the most pronounced seasonality, with almost

no linear relation to  $T_p$  in the summer and early fall months. The EIO even shows a reversed sign in July. The IOD index is less clearly related to  $T_p$  with opposite signs in the linear regression from the summer to winter season.

The goodness of the simple linear regression model is estimated by the root-mean-square errors of the 1-month lead forecast model (the standard deviation of the residual time series), which is smallest in the CIO region, indicating that this region fits best to the simple linear model (Fig. 1, gray area). It is interesting to note the two individual poles of the IOD fit better to the linear model than the IOD itself, which indicate that the IOD is indeed more independent of  $T_p$  than the individual poles. In summary, the parameters suggest that the CIO region may be the most predictable region and the IOD index would represent the least predictable index of those discussed here.

### b. Forecast results

The statistical model can be used to study the potential forecast skill for  $T_i$ . The forecast model in Eq. (1) is integrated over a 12-month lead, starting at each month of the time series from 1950 to 2007, assuming that the present  $T_i$  is known and the future  $T_p$  is either perfectly known or predicted with some exponentially decaying lead correlation skill, as it is found in most forecast schemas (e.g., Latif et al. 1998). For the imperfectly forecasted  $T_p$  we assume the following statistical characteristic:

$$T_p^f(t_0 + l) = a_{T_p}^l T_p(t_0 + l) + \sqrt{1 - a_{T_p}^{2l}} \xi(t_0), \quad (2)$$

where  $T_p^f$  is the imperfectly forecasted  $T_p$  at a forecast time lead  $l$ , with the forecast starting at time  $t_0$ ;  $a_{T_p}$  a scaling factor; and  $\xi$  a white noise forecast error with the same standard deviations as  $T_p$ . Equation (2) basically quantifies that the correlation of  $T_p^f$  with  $T_p$  decreases exponentially for increasing forecast lead times with a correlation to observed  $T_p$  of  $a_{T_p}^l$ . Additionally, it is assumed that the variance in  $T_p^f$  is the same as that of  $T_p$  for all lead times, resulting from some model forecast error  $\xi$ . Note that  $\xi$  is constant in  $l$ , meaning that for each forecast a systematic drift away from the true value is assumed, instead of fluctuations around the true  $T_p$ . This is a rather conservative assumption, resulting in significantly less skill than if  $\xi$  would be assumed to vary with lag time only. The scaling factor  $a_{T_p}$  is the assumed lag-1 forecast correlation skill of  $T_p^f$  relative to observed  $T_p$ . We choose  $a_{T_p} = 0.75^{1/12}$ , to mimic the results of LBMY07, who found that their 12-month lag correlation skill of  $T_p^f$  with  $T_p$  was 0.75. To estimate the forecast skills of the statistical model with imperfect forecasts of  $T_p$ , random values were used for  $\xi$ . For a smoother estimate of the correlation skill we calculated the skill values over 50 ensemble members with different realizations of  $\xi$ .<sup>1</sup>

For comparisons with the GCM modeling results in the literature we used cross-validated statistical estimates for the model parameters in Eq. (1) and for the definition of anomalies. Additionally, we estimated a linear

trend model by a simple cross-validated linear regression. Cross validation in all forecasts are achieved by estimating all statistical parameters over the time period before (after) the starting (ending) date of the forecast for all forecasts starting after (before) 1979 (the middle of the data period). We therefore reestimated all statistical parameters for each forecast starting date.

Figure 2 shows smoothed ensemble mean time series of different lead forecasts in comparison with the observed SST anomaly time series and the mean correlation skill values (based on the smoothed time series of all ensembles members) for 3-, 6-, and 9-month lead forecasts, assuming  $T_p$  is imperfectly forecasted at all lead times. The figure is kept in analogy to Fig. 3 in LBMY07. We find that the forecast skill of the simple model for the western Indian Ocean (WIO) index appears to be similar to those of LBMY07 (graphically evaluating Fig. 3 in LBMY07). It is interesting to note that some of the larger deviations of the 3–9-month lead forecasts of the WIO index in our statistical model, compared to the observed time series in 1984–85, 1988, 1992, and 1996, are similar to those of LBMY07, which may indicate that the models skills are due to the same predictor in the model, which could only be the Niño-3 SST. For the EIO region one may recognize a somewhat weaker agreement of the lead forecast with the observation than those in LBMY07 (e.g., 1994 negative peak). Subsequently, the superposition of WIO and EIO in the IOD index gives similar skills than those in LBMY07, though particularly the 1994 peak is again not as well forecasted as in LBMY07 because of the missing skill in forecasting the EIO.

LBMSY08 reported on a successful prediction of the 2006 IOD event. Figure 3 mimics Fig. 2 of LBMSY08, showing the forecast time series of the simple statistical model for 2006 and 2007 using imperfectly forecasted  $T_p$  and cross-validated statistics for the model again. While the forecast time series of WIO are qualitatively similar to those of LBMSY08, there are some noticeable differences in the forecast skill of the 2006 EIO negative anomaly. While LBMSY08 appear to have some skill in predicting this negative anomaly, there is no skill in the simple statistical model used in this study. Another interesting feature of this model is that forecasts that started at similar starting dates then end on the same forecast anomaly values, which is due to the fact that all of them use only Niño-3 SST as a predictor. A similar feature appears to be visible in LBMSY08 (in their Fig. 2), which may indicate that the forecast skill in their model is also mostly due to some external predictor, such as Niño-3 SST.

The forecast skill of the statistical model is quantified in terms of the anomaly correlation in Figs. 4a–d for perfectly and imperfectly forecasted  $T_p$ . Here the results

<sup>1</sup> Note that this is different from calculating the skill based on the ensemble mean prediction. The latter would, for large ensembles, produce forecasts with perfectly forecasted  $T_p$ , but only scaled by the constant factor  $a_{T_p}$ , and it is thus not comparable to GCM ensemble forecasts. Skill values estimated over the time series of all ensemble forecasts (not the ensemble mean) correspond to an imperfectly forecasted  $T_p$  as in an ensemble mean forecast of GCM simulations. In Fig. 2 we show the ensemble mean forecast, but the quoted skill values are again computed as a mean of the skill of the ensemble members.

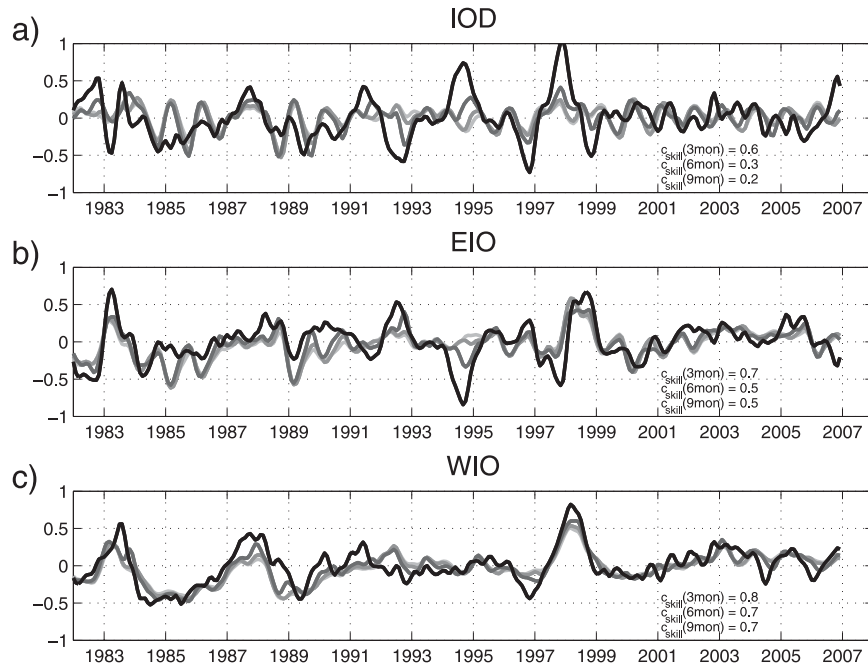


FIG. 2. Time series of the (a) IOD index, (b) EIO, and (c) WIO SST anomalies as observed (black lines), and the statistical model ensemble mean predictions at 3-, 6-, and 12-month leads (dark, medium, and light gray) with imperfectly forecasted  $T_p$  and cross-validated estimates of statistical parameters. Results have been smoothed with a 5-month running mean, as in Fig. 3 of LBMSY07. Correlation values of the predictions with the observed anomaly time series over the period shown are given in each panel. Note that the correlation values are based on the smoothed time series of all ensemble forecasts and not the ensemble mean. This value corresponds to an imperfectly forecasted  $T_p$  as in an ensemble mean forecast of a GCM simulation.

of the statistical model with both cross-validated statistics and all available statistics are presented. The CIO region has the best skill scores, indicating that it is the region most strongly forced by ENSO. Both the WIO and the EIO region have decent correlation skills on the order of 0.5–0.7 for one to two seasons lead forecast, which appears to be similar to those reported in LBMSY08 and LBMY07. The SWIO region shows correlation skills that are slightly below those found by Luo et al. (2005), which could indicate that the statistical model is missing some dynamical Indian Ocean response. The IOD index itself is the least predictable index, with very poor prediction skills, although it is still better than persistence. It may be noted here that the superposition of WIO + EIO (not shown) has much better correlation skills than the IOD (which is WIO – EIO). The skill values are comparable to those of the WIO index. This indicates that the coherent variability in WIO and EIO (a monopole superposition) is more strongly related to ENSO than the anticonherent variability (dipole superposition, IOD).

The seasonally resolved correlation skills (Fig. 5) show some clear seasonal dependence. The most predictable season for the WIO, CIO, and SWIO is the winter and late fall season. For the EIO, the winter and spring are

the most predictable seasons and the fall season is the least predictable season. The IOD seasonal predictability, however, does not reflect the seasonality of either the WIO or EIO regions. It peaks in late summer and fall and is least predictable in the seasons were WIO and EIO are most predictable. The results with respect to the CIO region are similar to those of the statistical model of Kug et al. (2004) for an index region similar to that of the CIO index. Overall the seasonality of this statistical model is similar to that found in the CGCM results of Wajsowicz (2005).

## 2. Summary and discussion

In this note the predictability of Indian Ocean SST indices, especially the IOD index, was studied with the help of a simple statistical forecast model. The aim of this study was to provide a simple forecast model, which can be used as a null hypothesis for Indian Ocean SST prediction skills, against which “dynamical” forecast skills of CGCM studies can be tested. The simple linear statistical model proposed as a null hypothesis for the Indian Ocean SST indices uses only the current Indian Ocean SST indices and the future Niño-3 SST as predictors. The



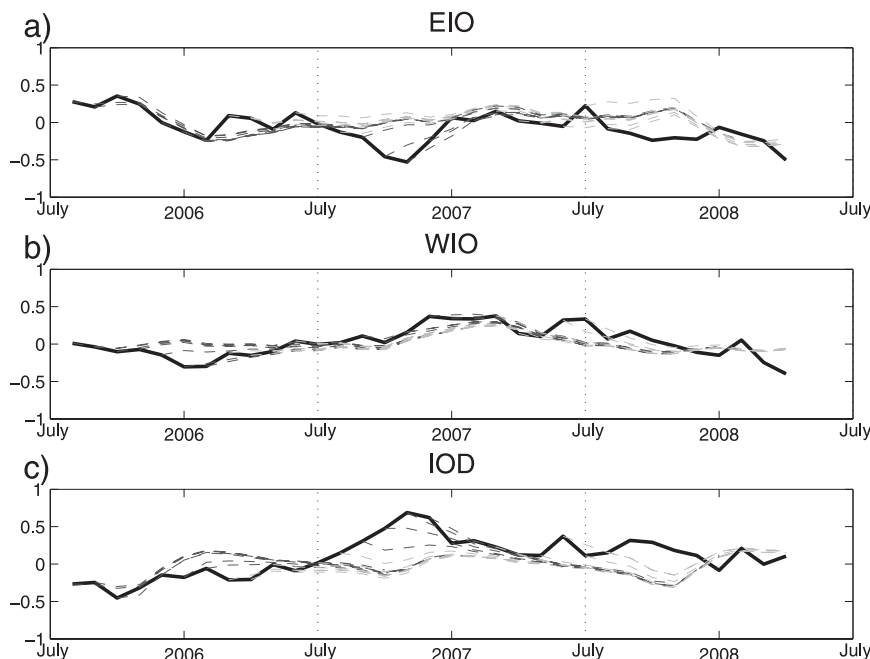


FIG. 3. As in Fig. 4, but for the years 2006–07, and the time series are not smoothed. The figure is in analogy to Fig. 2 in LBMSY08, but the IOD index time series is shown for completeness. The grayscale of the forecast time series change every 6 months.

parameters of this simple model were fitted to the observed data, and forecast skills over the time period of 1950–2007 were calculated.

The results of the simple model forecasts can first be summarized in terms of what the characteristics of a simple integration model in the Indian Ocean forced by Pacific SST would be, as follows:

- The correlation skill of 3–6-month lead forecasts are in the order of 0.5–0.7, depending on how well the Niño-3 SST can be predicted.
- The correlation skill varies with seasons because of the seasonality of El Niño and the Indian Ocean's response to it.
- The correlation skills are larger in all regions than persistence, indicating a significant influence of ENSO on all regions.
- The correlation skills are largest in the CIO region, which is slightly less in the SWIO region and significantly weaker in the EIO region.
- The IOD index is the least predictable index tested in this study with the simple statistical model. The correlation skills of the individual poles or the CIO region are much larger.
- The SST evolution can only be predicted, if significant SST anomalies in the tropical Pacific (here Niño-3 region) are present. This finding seems to be in good agreement with Song et al. (2008), who found a similar

characteristic in predicting IOD events in CGCM simulation.

The above-listed characteristics may be interpreted as a kind of null hypothesis for the prediction skill of Indian Ocean SST anomalies. However, it needs to be noted that the influence of the tropical Pacific SST is strongly simplified in the statistical model used here. The true influence may be more complex and may lead to larger skill values. In comparison to recent findings of CGCM studies the results can be summarized as follows:

- The overall correlation skills of 3–6-month lead forecast for the individual poles of the IOD and the IOD itself are generally comparable. This could indicate that the forecast skills found in the GCMs is only due to their correct representation of the remote forcing from the Pacific, and that therefore the Indian Ocean intrinsic dynamics independent of tropical Pacific SST as found in Fischer et al. (2005) and Behera et al. (2006) does not play a dominant role in the observed IOD index. Alternatively, the GCMs may have some predictability resulting from correctly resolved atmosphere–ocean dynamics within the Indian Ocean, but fail to adequately capture the coupling of the latter to Pacific SST anomaly (SSTA).
- The seasonality of the correlation skills of Wajsovicz (2005) and Kug et al. (2004) are similar to that found in the simple model used in this study.

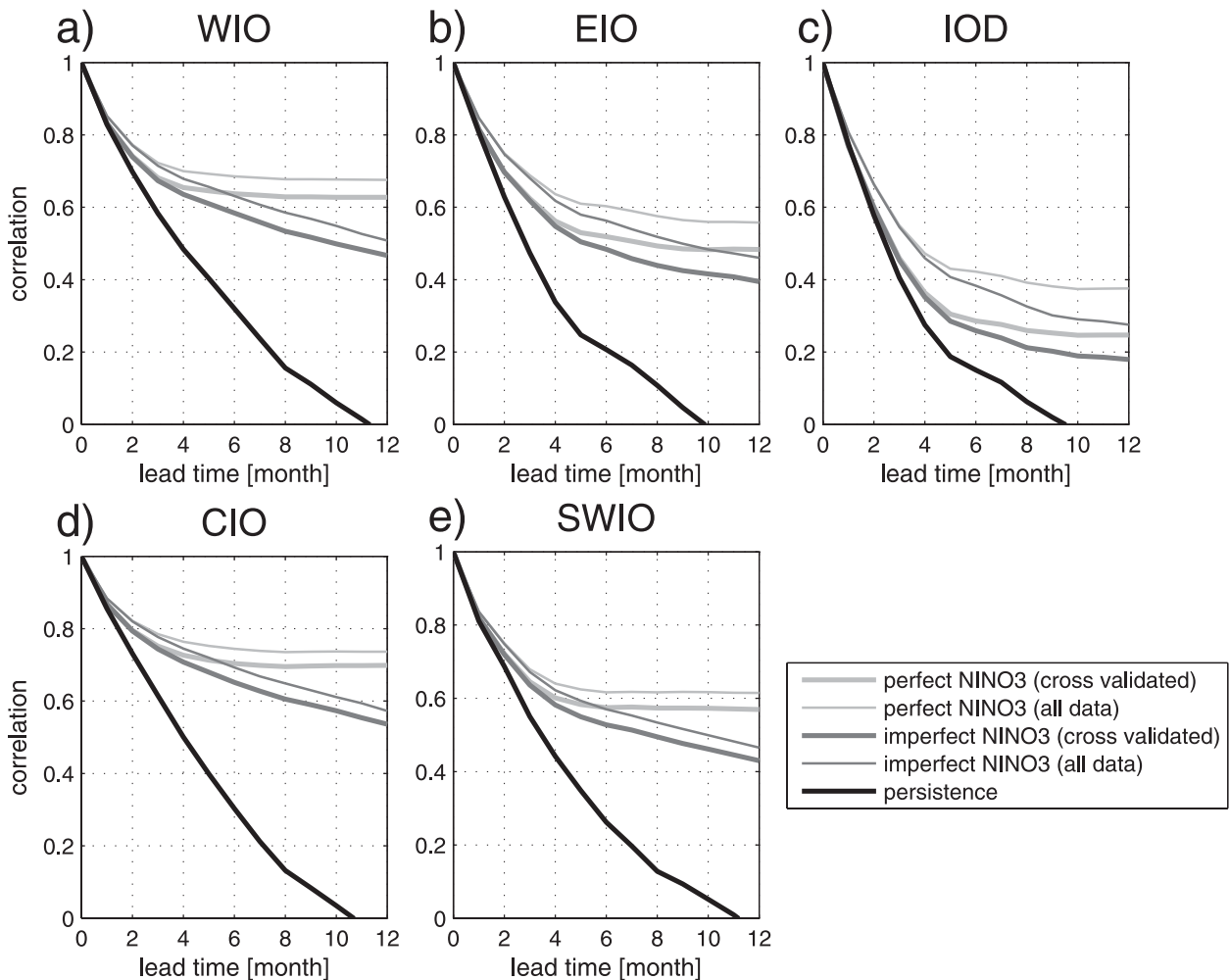


FIG. 4. Anomaly correlation skill values of the statistical forecast model for different linear detrended SST indices for the period of 1950–2007, assuming perfect forecast skill in  $T_p$  (light gray line), or assuming imperfectly forecasted  $T_p$  using the scaled  $T_p^f$  as described in the text (gray line) for cross-validated statistics (thick lines) and all available statistics (thin lines). For comparison the persistence skill (black line) is shown.

- Some of the larger deviations in the forecasts of LBM07 for the WIO region are similar in both models, which may indicate that both models are based on a similar predictor (Niño-3 SST).
- There is some indication that, during the 1994 and 2006 IOD events, the CGCM simulation of LBM07 and LBMSY08, respectively, could predict the EIO region better than the simple statistical forecast model, which indicates that the EIO region may have some dynamical forecast skill above the simple model proposed in this study for these events.
- The SWIO region also shows correlation skills slightly below those found by Luo et al. (2005), which may be a weak indication for Indian Ocean intrinsic SST variability independent of ENSO, caused by ocean dynamics of the shallow dome in this region (Schott et al. 2009).
- The results for the IOD index indicate no specific dynamical forecast skill for this index, which is not already found for the individual poles independent of each other. This suggests that it is more useful to split the IOD index into its eastern (EIO) and western (WIO) poles for prediction studies. The WIO is the more predictable pole index, which is mostly due to its response to Pacific SSTA. The EIO region, on the other hand, may have some predictability because of the Indian Ocean's intrinsic dynamics independent of tropical Pacific SST. The IOD index itself seems to be the least predictable index, which might be due to the rather independent mechanisms controlling each of the poles or may simply reflect that the IOD is, by construction, orthogonal to the leading monopole pattern, which is the type of pattern most strongly influenced by El Niño. It could, however, also reflect that dipoles in

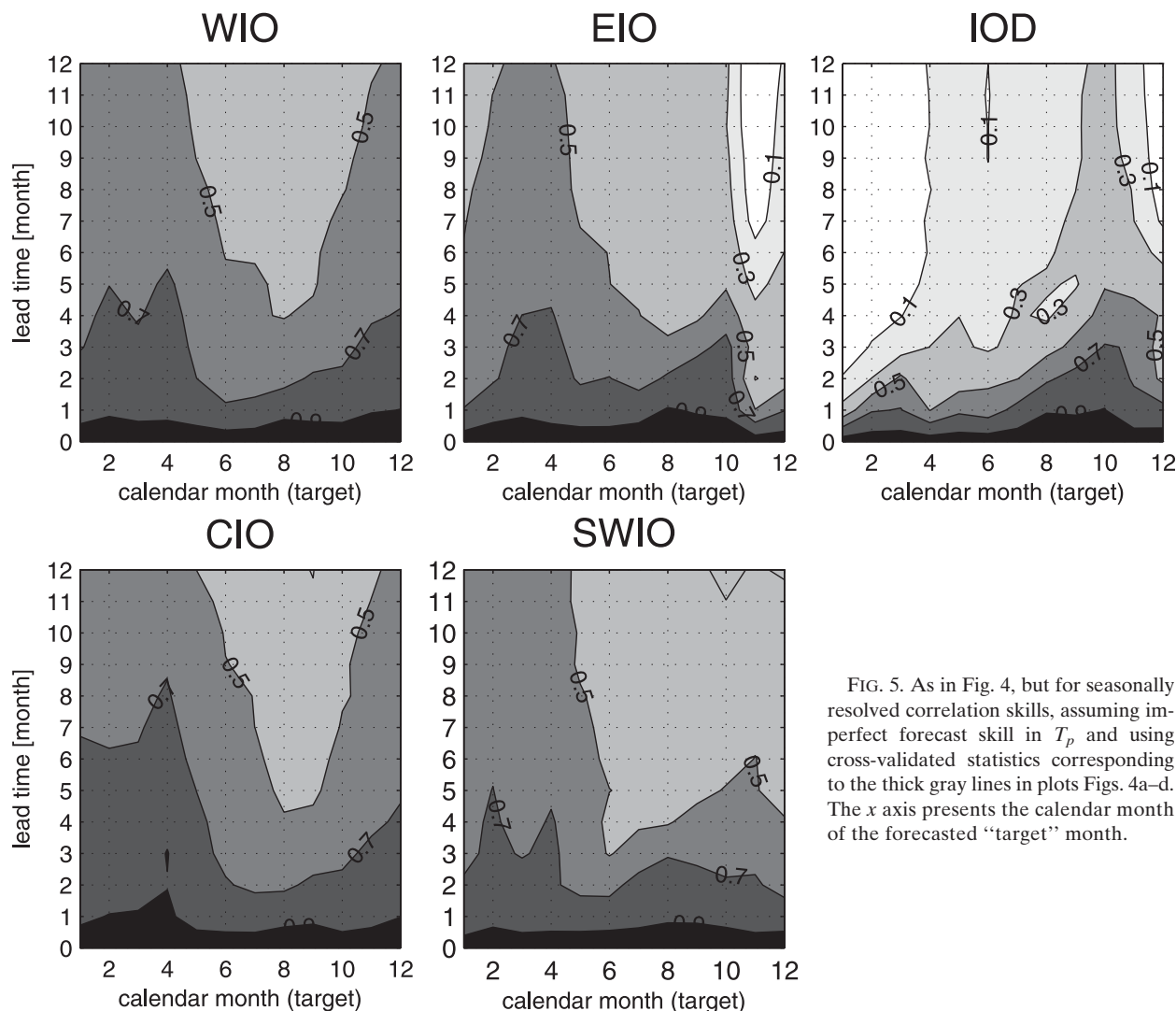


FIG. 5. As in Fig. 4, but for seasonally resolved correlation skills, assuming imperfect forecast skill in  $T_p$  and using cross-validated statistics corresponding to the thick gray lines in plots Figs. 4a–d. The  $x$  axis presents the calendar month of the forecasted “target” month.

general represent smaller spatial scales than monopole indices, which are in general less predictable.

It may seem unfair to compare this statistical forecast with CGCM forecasts, because the CGCM forecast schemes have to deal with much more complex problems, which will almost certainly lead to reduced forecast skill compared to what may theoretically be possible. Not only do current coarse-resolution CGCMs suffer from the limited physical presentation of the real world and subsequent limited representation of the true climate state, but they also suffer from limited observational data of, for instance, subsurface ocean conditions, which are assimilated into the CGCM forecast scheme. The assimilation scheme itself is another uncertainty in the forecast schemes, which degrade the forecast skill of current CGCM forecast schemes. One can therefore expect the forecast skills of the

CGCM simulation to improve in the future with improved physical presentation of the climate and improved observational data assimilation. However, at the current state of the art it seems that the reported forecast skills are not good enough for a clear evidence of dynamical forecast skill coming from the Indian Ocean intrinsic ocean dynamics, with some exception for the EIO index.

In summary, this study suggests that it is helpful for future studies of Indian Ocean SST predictions to directly compare the results of a complex CGCM forecast scheme with the simple null hypothesis formulated in this study. This allows us to better distinguish forecast skill resulting from Indian Ocean intrinsic ocean dynamics from forecast skill resulting essentially from the response to tropical Pacific SST anomalies, which could even be done for individual events, to pinpoint cases where Indian Ocean dynamics may have been important.



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